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#### **ABSTRACT**

In this study, two statistical approaches for adjusting grades were tested on data obtained from four law schools, with samples of 157, 188, 206, and 191. These approaches were previously validated using data on undergraduates but have not been used in a study of postgraduate performance. Neither method yielded consistent improvements in the predictive validity of Law School Admission Test (LSAT) scores and undergraduate grades. The single exception was for School D, where a significant improvement in the correlation of test scores with law school grades was observed. Two appendixes contain data from the law schools. (Contains 7 tables and 18 references.) (Author/SLD)



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- Statistical Adjustments of Law School Grade Point Averages

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# Statistical Adjustments of Law School Grade Point Averages

#### Abstract

In this study, two statistical approaches for adjusting grades were tested on data obtained from four law schools. These approaches were previously validated using data on undergraduates but have not been used in a study of postgraduate performance. Neither method yielded consistent improvements in the predictive validity of LSAT scores and undergraduate grades. The single exception was for School D where a significant improvement in the correlation of test scores with law school grades was observed.

#### Introduction

For any standardized testing program, one benchmark of the usefulness of the test scores is the validity of the scores to predict some important future outcome, a form of test validity known as predictive validity. In the case of LSAT scores, one important indicator of its predictive validity is in forecasting law school grades for enrolled students. As in many other situations concerned with the predictive validity of admissions information, institutional studies typically use multiple regression analysis to determine the validity of test scores and some prior measure of classroom performance (such as undergraduate grades) in predicting future academic performance (such as law school grades) for a cohort of students.

A vast literature exists on the prediction of academic performance, both at the undergraduate and postgraduate level (see e.g., Ramist (1985) and Schrader (1971) for summaries of the research over the past three decades). Earlier predictive validity studies of LSAT scores were conducted by Boldt (1976) and Linn and Hastings (1984).

One limitation of many past predictive validity studies, conducted both at colleges and at law schools, has been the reliance on first year grade point average (GPA) as the criterion (Wilson, 1983). The first year GPA has been favored in institutional studies because it is a well-defined criterion, it is easily obtainable from university records, and it is available relatively soon after the matriculation of a class of students. However, the first year GPA is neither a sufficient nor an adequate measure of a student's overall achievement. On the surface, the cumulative GPA computed across all semesters enrolled would appear to offer several advantages over the first year GPA as a criterion. However, few studies involving prediction of cumulative GPA have been conducted because the cumulative GPA is known to be a problematic criterion. Because each student's GPA is based on a different combination of courses, each with a unique grade distribution, the construct validity of the GPA scale is diminished. Hence, a criterion needs to be developed which takes into account the differences in course grading standards.

Criticisms about the effectiveness of preadmission measures generally focus only on the limitations of the predictors. However, the controversy over the validity of standardized tests has not properly taken into account the fact that the GPA criterion has certain correctable defects. One of the basic facts in measurement is that a variable with significant measurement error will have substantially reduced correlation with other measures (Cronbach, 1984). By statistically eliminating some of the unreliability in the grading process that results in course differences, we can expect that the apparent size of predictive validity coefficients will increase significantly.

This particular study of predicting law school academic performance was unique because it utilized two different statistical approaches developed by the author for adjusting the cumulative GPA. These two methods have been empirically tested on data relating undergraduate grades (Young, 1990, 1992) but have not been used in a study of postgraduate performance. The use of grade adjustment methods, both by the



author and by other researchers, has proven useful in understanding the observed phenomenon of differential predictive validity by gender and by race (Elliott & Strenta, 1988; Young, 1991a, 1991b).

Data for this study were obtained from four accredited law schools in the United States: two of the schools are located in the Northeast (Schools C and D), one is located in the South (School B), and the fourth is located in the West (School A). The names of the schools have been masked since identification of the specific institutions is not essential in understanding the results of this study. The cohort from each of these institutions is described below.

# The Participating Institutions

Three of the four law schools in this study, Schools B, C, and D, are affiliated with their state-supported flagship public university. The fourth law school, School A, is part of a private university which is church-affiliated. All four law schools are of moderate size with typical entering classes for the J.D. program of about 150–200 students per year. There is no assumption that these four schools are a representative sampling of any universe of law schools.

Data for School A (N = 157), School C (N = 188), and School D (N = 206) are for their respective entering classes of 1987 and would typically be expected to graduate in the Spring of 1990. Data for School B (N = 191) are for its entering class of 1989 with these students typically graduating in 1992. It would have been preferable to obtain data for the comparable cohort of students at School B as at the other institutions. However, due to extensive delays in obtaining data from School B, the information that was most readily available at the time of data collection was for its most recent cohort of graduates. Although the data from School B are somewhat more recent than for the other law schools, this does not appear to have substantially influenced the results of the study.

# The Adjustment Methods

The two statistical methods for adjusting grades used in this study are based on: (1) Item Response Theory (IRT), a measurement model, and (2) the General Linear Model (GLM), a statistical model. The first method yields an adjusted cumulative GPA known as the IRT-Based GPA; the second method yields an index called the LS-GPA (LS stands for Least-Squares). This terminology is consistent with that used in earlier studies using these two approaches. A brief description of the theory and development of each of these adjusted grade composites is given below. For a more complete treatment, the reader is referred to Young (1990, 1992). In addition to the two methods developed by the author, other researchers have developed similar methodologies for adjusting grades (see Young, 1993, for a relevant review).

#### The IRT-Based GPA

IRT was developed some forty years ago as an alternative to classical test theory in order to better handle some of the pressing problems in measurement that were unresolved. The author's doctoral dissertation (Young, 1989) is the first documented application of IRT to the problem of equating grades from different courses from the same institution onto a common scale. The IRT model used in this study is the rating scale version (Muraki, 1990) of Samejima's (1969) Graded Response Model (GRM). The GRM is an appropriate model for course grades because it appears likely that the underlying assumptions of the model can be met.

The data for this study correspond to an IRT framework in the following manner: Each student can be considered to be equivalent to an examinee, while each law school course can be considered equivalent to a test item with polytomous responses represented by the grade earned in that course. Since



students, primarily because they major in different fields, enroll for different combinations of courses, we are faced with a situation analogous to that found in matrix sampling testing programs where examinees attempt different sets of items. IRT is especially well-suited for handling this problem of creating a common metric regardless of which courses or items were taken.

The operating assumption of the GRM is that when an individual encounters a test item, a latent variable is induced. The probability that this variable takes on a value greater than the k-th category boundary depends on the person's ability, the value of the k-th category boundary, and the item's discrimination. In the rating scale version of the GRM, the distance between category boundaries is assumed to be equal across all items. The GRM has the following important advantage over models for dichotomous scoring: When data can be scored in three or more ordered categories, the model can yield a more precise estimate of an individual's ability than can be obtained by scoring data dichotomously.

The rating scale version of the Graded Response Model has the following form:

$$\pi_{nki} = \frac{\exp \left(\alpha_i \left(\Theta_n - \left(\beta_i + \tau_k\right)\right)\right)}{1 + \exp \left(\alpha_i \left(\Theta_n - \left(\beta_i + \tau_k\right)\right)\right)}$$

This expression is the probability of person n scoring k or more on item i, where  $\alpha_i$  is the discrimination parameter of item i,  $\Theta_n$  is the ability parameter of person n,  $\beta_i$  is the location parameter of item i, and  $\tau_k$  is the value of the k-th category boundary between categories k and k+1. The k-th category boundary,  $\tau_k$ , is the point on the ability scale where responding in or above category k has probability equal to .5.

The Graded Response Model does not provide a simple general expression for the probability  $\pi_{nki}$  of person n responding in category k to item i. Instead, this probability is obtained by subtracting cumulative probabilities for all of the categories. In addition, the GRM does not allow for the algebraic separation of person and item parameters. Thus, no sufficient statistic can be derived for either person or item parameters in this model.

In the context of this study, the ability parameter for a given student is estimated based on the grades received in law school courses. For a specific course, the location parameter represents its relative difficulty among the courses at that law school, the discrimination parameter represents the increment in ability needed to obtain successively higher grades, and the category boundaries represent the relative distance among the different levels of grades. Simply stated, the GRM estimates each individual's ability based on all of the grades earned with each grade weighted by the actual frequency distribution of grades in each course. The same grade earned in a course with proportionately fewer high grades is considered more valuable than one earned in a course with a larger proportion of high grades, all other factors held constant. The estimated ability level from the GRM is a non-linear transformation of the actual GPA.

#### The Least-Squares GPA

The second method, based on GLM using classical least-squares techniques, is the most powerful of all statistical models (see e.g., Searle, 1971). When used to obtain a statistically adjusted GPA, the GLM takes the form of an incomplete design. Multiple measurements for each student (i.e., block) is available in the form of course grades. Each unique college course is considered the equivalent of a treatment. An estimate of the effect due to each course can be obtained and used to compute an adjusted cumulative GPA for each student. This method has certain advantages over the IRT-based method in that it generally requires less computing time, and also generates somewhat more stable estimates.



In computing the LS-GPA, an estimate of the effect due to each course is obtained and used to compute an adjusted cumulative GPA for each student. In this study, the GLM is an additive model with main effects only and has the following form:

$$GRADE_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}$$
,

where  $GRADE_{ij}$  is the numerical value of the letter grade for the i-th student in the j-th course,  $\mu$  is the grand mean of course grades,  $\alpha_i$  is the 'effect' due to the i-th student,  $\beta_j$  is the 'effect' due to the j-th course, and  $\epsilon_{ij}$  is the error term. Quotations are used around the word effect since this study does not satisfy the requirements for a true experimental study and no causal mechanism is postulated. Note that in this model, there is no interaction term,  $(\alpha\beta)_{ij}$ , since each student only takes each course once. Thus, estimation of this parameter is not possible since in this model it is absorbed into the error term.

The sample estimates of the parameters for the GLM are given by:

GRADE 
$$'_{ij} = \overline{X}.. + \hat{\alpha}_i + \hat{\beta}_j$$
.

To compute an adjusted GPA for each student, we need an estimate of the average grading 'effect' due to each student. This estimate is given by the following expression:

$$\hat{\alpha}_i = (\sum_j (GRADE'_{ij} - \overline{X}.. - \hat{\beta}_j)) / j$$
.

It should be noted that the students-by-courses data matrix in this study does not meet some of the assumptions for a randomized design. First, random assignment of students to courses is impossible for obvious reasons. In addition, the assumption of no student-by-course interactions may be violated since a student's grade may be determined by factors other than course performance, such as judicious course selection. Nevertheless, the advantage of this approach is that it enables us to develop a statistical procedure for adjusting a student's GPA. In contrast to the GRM, the GLM estimates each individual's ability based on all of the grades earned with each grade weighted by the mean of the grades in each course.

### Methodology

The data for this study were obtained from the registrar's office of each law school and were made available in the form of a computer tape. The process for creation of this tape was essentially the same at all four institutions: Data on preadmission measures, LSAT scores and undergraduate GPA, were merged with law school course data and written to tape along with a pseudo student identification number (to preserve anonymity). For Schools C and D, undergraduate GPA was not obtainable.

The methods used to compute the adjusted GPAs were similar to those of previous studies. For the Least-Squares GPA, courses in which five or more students earned a letter grade were included. For each law school, the following number of courses was used to compute this index: School A, 142, School B, 169, School C, 173, and School D, 158. For the IRT-based GPA, the 50 courses at each institution with the highest number of enrolled students earning letter grades were used. As is true of earlier studies that used these methods, the number of courses was restricted due to the computation limitations of the statistical software.



For the IRT-based GPA, ordered categories of letter grades were used to estimate parameter values; for the LS-GPA, the letter grades were converted to their numerical equivalents using each institution's grading system. Non-letter grades such as Incomplete, No Credit, and Pass are excluded from the calculation of the IRT-based GPA, the LS-GPA, and the standard GPA. The data matrices used to calculate the adjusted GPAs are constructed as follows: the rows of each matrix represent students at a given law school while the columns represent courses taken by the cohort of students. The cells of each matrix contain the grade of a particular student in a specific course. If a student did not enroll in a course or did not receive a letter grade, a missing value was assumed for that cell of the matrix.

The data were checked for accuracy prior to usage and formatted for the various computer programs. Descriptive statistics were calculated for selected variables and predictive validity results are obtained in the standard manner by using multiple regression analysis to predict GPAs from the preadmissions measures. MULTILOG (Thissen, 1988) was the FORTRAN computer program used for estimating parameters of the Graded Response Model used to calculate the IRT-based GPA. PROC GLM in SAS (SAS Institute, Inc., 1985) was used for data management and to compute the Least-Squares GPA. All analyses were conducted using computer facilities available at Rutgers University.

#### Results

The results from this study are displayed in Tables 1-7 on the following pages with a discussion in the next section. Table 1 lists means and standard deviations for selected variables. Note that the grading system used at Schools B, C, and D is the traditional 4-point scale where an A is equivalent to a 4.0. In contrast, grades at School A range from a low of 50 to a high of 90. This difference in the grading systems has no impact on later results.

Table 1
Means and Standard Deviations of Variables

	School A	School B	School C	School D
N	157	191	188	206
LSAT	35.27 (4.72)	38.24 (4.68)	34.70 (4.76)	34.46 (6.44)
UGPA	3.40 (0.33)	3.22 (0.37)		
LAWGPA	74.69 (3.26)	2.88 (0.33)	2.92 (0.45)	2.98 (0.45)

Note: UGPA = undergraduate GPA, LAWGPA = law school GPA.

Note: Entries are means with standard deviations underneath in parentheses.



Correlational and predictive validity results are displayed for School A in Tables 2 and 3; for School B in Tables 4 and 5; for School C in Table 6; and for School D in Table 7. Note that the sample sizes for these results is slightly different from that given in Table 1. This is due to missing data for a few cases for one or more of the variables in these analyses.

Table 2
Institution: School A (N = 152)

# Matrix of Correlation Coefficients

	LSAT	UGPA	LAWGPA	LSGPA	IRTGPA
LSAT	1.00	•			
UGPA	.09	1.00			
LAWGPA	.41	.39	1.00	•	
LSGPA	.40	.40	.99	1.00	
IRTGPA	.41	.35	.97	.97	1.00



Table 3
Institution: School A (N = 152)

Prediction Equations Using Preadmission Measures

Dependent Variable: LAWGPA (Law School GPA)

		Analys	is of Variance	Source Table	
Source	df	SS	MS	F-ratio	R <sup>2</sup>
Model Error Total	2 149 151	463.70 1139.70 1603.40	231.85 7.65	30.31	.2892

_	Multiple Regression Analysis Parameter Estimates				
Variable	Estimate	Std Error	t-statistic	p <	
intercept	53.6854	2.7697	19.38	.0001	
LSAT	0.2568	0.0479	5.37	.0001	
UGPA	_ 3.5170	0.6870	5.12	.0001	

Dependent Variable: LSGPA (Least-Squares GPA)

		Analysis of Variance Source Table				
Source	df	SS	MS	F-ratio	R <sup>2</sup>	
Model Error	2 149	488.43 1157.69	244.22 7.77	31.43	.2967	
Total	151	1646.12				

 Multiple Regression Analysis Parameter Estimates

 Variable
 Estimate
 Std Error
 t-statistic
 p <</th>

 intercept
 54.1946
 2.7914
 19.42
 .0001

 LSAT
 0.2587
 0.0482
 5.36
 .0001

 UGPA
 3.6803
 0.6924
 5.32
 .0001

Dependent Variable: IRTGPA (Item Response Theory GPA)

		Analys	is of Variance	Source Table	
Source	df	SS	MS	F-ratio	R <sup>2</sup>
Model Error Total	2 149 151	28.55 79.08 107.63	14.28 0.53	26.90	.2653

_	Multiple Regression Analysis Parameter Estimates				
Variable	Estimate	Std Error	t-statistic	p <	
intercept LSAT UGPA	-5.1511 0.7962 0.0685	0.7296 0.1810 0.0126	-7.06 4.40 5.44	.0001 .0001 .0001	



Table 4
Institution: School B (N = 190)

# Matrix of Correlation Coefficients

	LSAT	UGPA	LAWGPA	LSGPA	IRTGPA
LSAT	1.00			•	
UPGA	06	1.00			
LAWGPA	.46	.18	1.00		
LSGPA	.45	.19	.98	1.00	
IRTGPA	.46	.13	.91	.91	1.00



Table 5
Institution: School B (N = 190)

Prediction Equations Using Preadmission Measures

Dependent Variable: LAWGPA (Law School GPA)

		Analys	sis of Variance	Source Table	
Source	df	SS	MS	F-ratio	R <sup>2</sup>
Model Error Total	2 187 189	5.17 15.27 20.44	2.58 0.08	31.63	.2528

Multiple Regression Analysis Parameter Estimates Variable **Estimate** Std Error t-statistic p < intercept 1.0103 0.2578 3.92 .0001 **LSAT** 0.0330 0.0044 7.42 .0001 **UGPA** 0.1877 0.0566 3.32 .0001

Dependent Variable: LSGPA (Least-Squares GPA)

Analysis of Variance Source Table Source  $\mathbb{R}^2$ df SS MS F-ratio 5.88 17.55 Model 5.88 31.34 .2511 187 0.09 Error Total 189 23.44

Multiple Regression Analysis Parameter Estimates Variable Estimate Std Error t-statistic p < intercept 1.0141 0.2764 3.67 .0003 LSAT 0.0349 0.0048 7.32 .0001 **UGPA** 0.2115 0.0607 3.48 .0006

Dependent Variable: IRTGPA (Item Response Theory GPA)

Analysis of Variance Source Table

Source	df	SS	MS	F-ratio	R <sup>2</sup>
Model Error Total	2 187 189	8.40 27.01 35.41	4.20 0.14	29.08	.2372

Multiple Regression Analysis Parameter Estimates

Variable	<u>Estimate</u>	Std Error	t-statistic	p <
intercept	-1.6384	0.3429	-4.78	.0001
LSAT	0.0434	0.0059	7.33	.0001
UGPA	0.1919	0.0752	2.55	.0116



Table 6
Institution: School C (N = 178)

# Matrix of Correlation Coefficients

	LSAT	<u>LAWGPA</u>	LSGPA_	IRTGPA
LSAT LAWGPA LSGPA IRTGPA	1.00 .43 .42 .34	1.00 .99 .90	1.00 .89	1.00

Prediction Equations Using Preadmission Measures

Dependent Variable: LAWGPA (Law School GPA)

<u>Analysis</u>	of '	<u>Variance</u>	Source	Table

Source	df	SS	MS	F-ratio	R <sup>2</sup>
Model Error Total	1 176 177	6.70 29.98 36.69	6.70 0.17	39.38	.1828

Multiple Regression Analysis Parameter Estimates

Variable	Estimate	Std Error	t-statistic	p <
intercept	1.5078	0.2284	6.60	.0001
LSAT	0.0409	0.0065	6.28	.0001

Dependent Variable: LSGPA (Least-Squares GPA)

# Analysis of Variance Source Table

-			/	Dourte Tubie	
Source	<u>df</u>	SS	MS	F-ratio	R <sup>2</sup>
Model Error Total	1 176 177	6.73 31.09 37.82	6.73 0.18	38.13	.1781

# Multiple Regression Analysis Parameter Estimates

Variable	<u>Estimate</u>	Std Error	t-statistic	p <
intercept	1.6105	0.2326	6.92	.0001
LSAT	0.0410	0.0066	6.18	.0001

Dependent Variable: IRTGPA (Item Response Theory GPA)

# Analysis of Variance Source Table

-				BULLIU I GOIC	
Source	df	SS	MS	F-ratio	R <sup>2</sup>
Model Егтог Total	1 176 177	3.14 24.16 27.30	3.14 0.14	22.87	.1150

# Multiple Regression Analysis Parameter Estimates

Variable	Estimate	Std Error	t-statistic	p <
intercept	-1.0748	0.2051	-5.24	.0001
LSAT	0.0280	0.0059	4.78	



Table 7
Institution: School D (N = 181)

#### Matrix of Correlation Coefficients

	LSAT	LAWGPA	<u>LS</u> GPA	IRTGPA
LSAT	1.00			
LAWGPA	.63	1.00		
LSGPA	.67	.99	1.00	
IRTGPA	.65	.92	.91	1.00

#### Prediction Equations Using Preadmission Measures

Dependent Variable: LAWGPA (Law School GPA)

Analysis of Variance Source Table Source df R<sup>2</sup> SS MS F-ratio Model 14.42 14.42 .4009 119.78 Error 179 21.55 0.12 **Total** 180 35.98

Multiple Regression Analysis Parameter Estimates Variable Estimate Std Error t-statistic p < intercept 1.4672 0.1407 10.43 .0001 LSAT 0.0440 0.0040 10.94 .0001

Dependent Variable: LSGPA (Least-Squares GPA)

Analysis of Variance Source Table Source  $\mathbb{R}^2$ df SS MS F-ratio Model 17.21 17.21 147.17 .4512 179 20.93 Error 0.12 38.14 Total 181

Multiple Regression Analysis Parameter Estimates Variable Estimate Std Error t-statistic p < 1.4434 intercept 0.1387 10.41 .0001 LSAT 0.0481 0.0040 12.13 .0001

Dependent Variable: IRTGPA (Item Response Theory GPA)

Analysis of Variance Source Table Source df  $\mathbb{R}^2$ SS MS F-ratio Model 26.28 36.38 26.28 129.33 .4194 179 **Error** 0.20 Total 180 62.66

 Multiple Regression Analysis Parameter Estimates

 Variable
 Estimate
 Std Error
 t-statistic
 p <</th>

 intercept LSAT
 -2.5477
 0.1828
 -13.94
 .0001

 LSAT
 0.0594
 0.0052
 11.37
 .0001



#### **Descriptive Statistics**

The average of LSAT scores for the cohorts from Schools A, C, and D are quite similar, around 35, while the average for School B is significantly higher at 38.24 (p < .05). The variation in scores, as measured by the standard deviation, is around 4.7 for Schools A, B, and C while School D has greater variability in scores with a standard deviation of 6.44 (p < .05). It is likely that the greater variation of scores at School D leads to a higher correlation of LSAT scores with law school grades than is true for the other institutions. This point is further elaborated in the discussion section.

# Results of Adjusting Grades

Representative results from adjusting grades via IRT and GLM, for School D, are given in the appendices at the end of this report. Grade adjustment via IRT yielded a measure of law school performance for each student, labeled THETAHAT on the printout, that is standardized within each institution to have a normal distribution with a mean of zero and a variance of one (see appendix A). Although this scale differs from the grade scales used by the law schools, this difference has no effect on the correlational or predictive validity results. Only IRT results for individuals are presented since comparison among courses is not central to this study. In contrast, the adjustment via GLM yielded the LS-GPA which is standardized to have the same mean and variance as the actual distribution of GPAs at each law school (see appendix B). Values for grades in appendix B are those reported on the institution's computer tape; actual grades are these values divided by ten (this computation does not impact correlational or predictive validity results).

# Correlational and Predictive Validity Results

In general, the effects of adjusting law school GPA (LAWGPA) via IRT is greater than using Least-Squares. This is evident by comparing the correlations of LAWGPA with IRTGPA (range: .90 - .97) and LAWGPA with LS-GPA (range: .98 - .99). Neither adjustment method, however, yields consistently higher correlations of grades with LSAT scores. The unweighted average correlation of LSAT scores with LAWGPA is .48 (range: .41 - .63); of LSAT scores with IRTGPA is .47 (range: .34 - .65); and of LSAT scores with LS-GPA is .49 (range: .40 - .67). The largest impact due to adjusting grades occurs at School D where the correlation of LSAT scores with LAWGPA is .63 but is significantly higher with LS-GPA at .67 (p < .001).

The effects of adjusting law school grades in terms of their correlation with undergraduate grades is mixed. For the two institutions for which undergraduate GPAs were available, Schools A and B, the IRT method yields a lower correlation while the Least-Squares approach yields a minimal increase in correlation. At both institutions, LSAT scores have a significantly higher correlation with LAWGPA, IRTGPA, and LS-GPA when compared with undergraduate GPA. Since both undergraduate grades and LSAT scores were available for Schools A and B, an analysis of the multiple correlation of these preadmission measures with grades is possible. These values range from a low of .49 with IRTGPA at School B to a high of .54 for LS-GPA and LAWGPA at School A which are generally similar to predictive validity results from studies conducted at other law schools (see e.g., Linn & Hastings, 1984).

An interpretation of the results of this study is provided in the next section.



#### Discussion

In general, the two grade adjustment methods applied to these data appear to yield relatively minor improvements in the predictive validity of LSAT scores in forecasting law school academic performance with one exception: the use of the Least-Squares approach significantly raised the correlation of LSAT scores from .63 to .67 at School D. The most plausible explanation for the apparent lack of improvement is the high commonality of the courses taken by these students. Since the students at each law school enrolled in essentially the same courses, any adjustment method based on course differences will likely have little impact in changing the relative rankings of students. In contrast, undergraduates generally have greater latitude in choosing courses and majors, thus the apparent improvement from use of these methods is substantially greater.

The significant improvement found for LS-GPA at School D is most likely due to the fact that the variation in LSAT scores is significantly greater than at the other institutions. A comparison of the variance (the square of the standard deviation) of test scores shows that School D has at least 83% greater variance in scores than at any of the other law schools. In other words, the smaller variance of LSAT scores at Schools A, B, and C means that the likely restriction of range in these scores leads to decreased correlations with other variables.

Finally, it also appears that of the two methods, the Least-Squares approach was generally better for these data and yielded results that were expected and in the right direction. The Least-Squares approach is conceptually simpler and computationally less demanding to implement, reasons that may have led to the results found here.



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Appendix A



MULTILOG

FOR MULTIPLE CATEGORICAL ITEM RESPONSE DATA

VERSION 5.11

LSAT Study - School D

**DATA PARAMETERS** 

N L L1 L2 NCHAR MCODE 206 51 50 1 4 9

**ESTIMATION PARAMETERS-**

 NCYC
 NFRC
 NSEG
 NP
 MAXIT

 100
 0
 1
 0
 10

I/O CONTROLS

LOTS I1 I2 RESTRT 0 1 2 0

CONVERGENCE CONTROL-

CRTI CRTC STEP RK RM ACCMAX .001 .0010 .5000 .9000 1.0000 .0000

MISSING VALUE CODE FOR CONTINUOUS DATA= 9.0000

SWITCHES-

PUNI **PUNS PRNTS** READI READS FIT SCORE KMID SDIZE **READC** F F T T T F T F F F MARG **RWT** INCORE **PRIOR** F F F F



#### ITEM SUMMARY AT START

#### SCHOOL D

#### ITEM 1 9 GRADED CATEGORIES

# A = P( 1) = 1.000 B( 1) = P( 2) = -2.080 B( 2) = P( 3) = -1.250 B( 3) = P( 4) = -.693 B( 4) = P( 5) = -.223

$$B(5) = P(6) = .223$$

$$B(6) = P(7) = .693$$

$$B(7) = P(8) = 1.250$$

$$B(8) = P(9) = 2.080$$

#### ITEM 2 9 GRADED CATEGORIES

$$A = P(10) = 1.000$$

$$B(1) = P(11) = -2.080$$

$$B(2) = P(12) = -1.250$$

$$B(3) = P(13) = -.693$$

$$B(4) = P(14) = -.223$$

$$B(5) = P(15) = .223$$

$$B(6) = P(16) = .693$$

$$B(7) = P(17) = 1.250$$

$$B(8) = P(18) = 2.080$$

#### ITEM 3 9 GRADED CATEGORIES

#### A = P(19) = 1.000

$$B(1) = P(20) = -2.080$$

$$B(2) = P(21) = -1.250$$

$$B(3) = P(22) = -.693$$

$$B(4) = P(23) = -.223$$

$$B(5) = P(24) = .223$$
  
 $B(6) = P(25) = .693$ 

$$B(7) = P(26) = 1.250$$

$$B(7) - F(20) - 1.230$$

$$B(8) = P(27) = 2.080$$

#### ITEM 4 9 GRADED CATEGORIES

# A = P(28) = 1.000

$$B(1) = P(29) = -2.080$$

$$B(2) = P(30) = -1.250$$

$$B(3) = P(31) = -.693$$

$$B(4) = P(32) = -.223$$

$$B(5) = P(33) = .223$$

$$B(6) = P(34) = .693$$

$$B(7) = P(35) = 1.250$$

$$B(8) = P(36) = 2.080$$

#### ITEM 5 9 GRADED CATEGORIES

$$A = P(37) = 1.000$$

$$B(1) = P(38) = -2.080$$

$$B(2) = P(39) = -1.250$$

$$B(3) = P(40) = -.693$$

$$B(4) = P(41) = -.223$$

$$B(5) = P(42) = .223$$

$$B(6) = P(43) = .693$$

$$B(7) = P(44) = 1.250$$

$$B(8) = P(45) = 2.080$$

# ITEM 6 9 GRADED CATEGORIES

#### A = P(46) = 1.000

$$B(1) = P(47) = -2.080$$

$$B(2) = P(48) = -1.250$$

$$B(3) = P(49) = -.693$$

$$B(4) = P(50) = -.223$$

$$B(5) = P(51) = .223$$

$$B(6) = P(52) = .693$$
  
 $B(7) = P(53) = 1.250$ 

$$B(8) = P(54) = 2.080$$

### ITEM 7 9 GRADED CATEGORIES

# A = P(55) = 1.000

$$B(1) = P(56) = -2.080$$

$$B(2) = P(57) = -1.250$$

$$B(3) = P(58) = -.693$$

$$B(4) = P(59) = -.223$$
  
 $B(5) = P(60) = .223$ 

$$B(6) = P(61) = .693$$

$$B(7) = P(62) = 1.250$$

$$B(8) = P(63) = 2.080$$

#### ITEM 8 9 GRADED CATEGORIES

# A = P(64) = 1.000

$$B(1) = P(65) = -2.080$$

$$B(2) = P(66) = -1.250$$

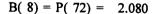
$$B(3) = P(67) = -.693$$

$$B(4) = P(68) = -.223$$

$$B(5) = P(69) = .223$$

$$B(6) = P(70) = .693$$

$$B(7) = P(71) = 1.250$$





#### ITEM 9 9 GRADED CATEGORIES

A = P(73) = 1.0	000
B(1) = P(74) =	-2.080
B(2) = P(75) =	-1.250
B(3) = P(76) =	693
B(4) = P(77) =	223
B(5) = P(78) =	.223
B(6) = P(79) =	.693

B(7) = P(80) = 1.250

B(8) = P(81) = 2.080

### ITEM 10 9 GRADED CATEGORIES

A = P(82) = 1.0	00
B(1) = P(83) =	-2.080
B(2) = P(84) =	-1.250
B(3) = P(85) =	693
B(4) = P(86) =	223
B(5) = P(87) =	.223
B(6) = P(88) =	.693
B(7) = P(89) =	1.250
B(8) = P(90) =	2.080

# ITEM 11 9 GRADED CATEGORIES

### ITEM 12 9 GRADED CATEGORIES

A = P(100) = 1.0	00
B(1) = P(101) =	-2.080
B(2) = P(102) =	-1.250
B(3) = P(103) =	693
B(4) = P(104) =	223
B(5) = P(105) =	.223
B(6) = P(106) =	.693
B(7) = P(107) =	1.250
B(8) = P(108) =	2.080

# ITEM 13 9 GRADED CATEGORIES

#### ITEM 14 9 GRADED CATEGORIES

A = P(118) = 1.0	00
B(1) = P(119) =	-2.080
B(2) = P(120) =	-1.250
B(3) = P(121) =	693
B(4) = P(122) =	223
B(5) = P(123) =	.223
B(6) = P(124) =	.693
B(7) = P(125) =	1.250
B(8) = P(126) =	2.080

# ITEM 15 9 GRADED CATEGORIES

A = P(127) = 1.0	00
B(1) = P(128) =	-2.080
B(2) = P(129) =	-1.250
B(3) = P(130) =	693
B(4) = P(131) =	223
B(5) = P(132) =	.223
B(6) = P(133) =	.693
B(7) = P(134) =	1.250
B(8) = P(135) =	2.080

# ITEM 16 9 GRADED CATEGORIES

A = P(136) =	1.000	
B(1) = P(137)	= -2.08	30
B(2) = P(138)	= -1.25	0
B(3) = P(139)	=69	3
B(4) = P(140)	=22	3
B(5) = P(141)	= .22	3
B(6) = P(142)	= .69	3
B(7) = P(143)	= 1.25	0
B(8) = P(144)	= 2.08	0



#### ITEM 17 9 GRADED CATEGORIES

# A = P(145) = 1.000 B(1) = P(146) = -2.080 B(2) = P(147) = -1.250 B(3) = P(148) = -.693 B(4) = P(149) = -.223 B(5) = P(150) = .223 B(6) = P(151) = .693 B(7) = P(152) = 1.250

B(8) = P(153) = 2.080

# ITEM 18 9 GRADED CATEGORIES

# ITEM 19 9 GRADED CATEGORIES

#### ITEM 20 9 GRADED CATEGORIES

A = P(172) = 1.00	00
B(1) = P(173) =	-2.080
B(2) = P(174) =	-1.250
B(3) = P(175) =	693
B(4) = P(176) =	223
B(5) = P(177) =	.223
B(6) = P(178) =	.693
B(7) = P(179) =	1.250
B(8) = P(180) =	2.080

### ITEM 21 9 GRADED CATEGORIES

```
A = P(181) = 1.000

B(1) = P(182) = -2.080

B(2) = P(183) = -1.250

B(3) = P(184) = -.693

B(4) = P(185) = -.223

B(5) = P(186) = .223

B(6) = P(187) = .693

B(7) = P(188) = 1.250

B(8) = P(189) = 2.080
```

#### ITEM 22 9 GRADED CATEGORIES

A = P(190) = 1.0	00
B(1) = P(191) =	-2.080
B(2) = P(192) =	-1.250
B(3) = P(193) =	693
B(4) = P(194) =	223
B(5) = P(195) =	.223
B(6) = P(196) =	.693
B(7) = P(197) =	1.250
B(8) = P(198) =	2.080

# ITEM 23 9 GRADED CATEGORIES

A = P(199) = 1.0	00
B(1) = P(200) =	-2.080
B(2) = P(201) =	-1.250
B(3) = P(202) =	693
B(4) = P(203) =	223
B(5) = P(204) =	.223
B(6) = P(205) =	.693
B(7) = P(206) =	1.250
B(8) = P(207) =	2.080

# ITEM 24 9 GRADED CATEGORIES

A = P(208) = 1.0	00
B(1) = P(209) =	-2.080
B(2) = P(210) =	-1.250
B(3) = P(211) =	693
B(4) = P(212) =	223
B(5) = P(213) =	.223
B(6) = P(214) =	.693
B(7) = P(215) =	1.250
B(8) = P(216) =	2.080



#### ITEM 25 9 GRADED CATEGORIES

# ITEM 29 9 GRADED CATEGORIES

- A = P(217) = 1.000B(1) = P(218) = -2.080
- B(2) = P(219) = -1.250
- B(3) = P(220) = -.693
- B(4) = P(221) = -.223
- B(5) = P(222) = .223
- B(6) = P(223) = .693
- B(7) = P(224) = 1.250
- B(8) = P(225) = 2.080

#### ITEM 26 9 GRADED CATEGORIES

# A = P(226) = 1.000

- B(1) = P(227) = -2.080
- B(2) = P(228) = -1.250
- B(3) = P(229) = -.693
- B(4) = P(230) = -.223
- B(5) = P(231) = .223
- B(6) = P(232) = .693
- B(7) = P(233) = 1.250
- B(8) = P(234) = 2.080

# ITEM 27 9 GRADED CATEGORIES

#### A = P(235) = 1.000

- B(1) = P(236) = -2.080
- B(2) = P(237) = -1.250
- B(3) = P(238) = -.693
- B(4) = P(239) = -.223
- B(5) = P(240) = .223
- B(6) = P(241) = .693
- B(7) = P(242) = 1.250
- B(8) = P(243) = 2.080

#### ITEM 28 9 GRADED CATEGORIES

# A = P(244) = 1.000

- B(1) = P(245) = -2.080
- B(2) = P(246) = -1.250
- B(3) = P(247) = -.693
- B(4) = P(248) = -.223
- B(5) = P(249) = .223
- B(6) = P(250) = .693
- B(7) = P(251) = 1.250
- B(8) = P(252) = 2.080

# B(2) = P(255) = -1.250 B(3) = P(256) = -.693 B(4) = P(257) = -.223

B(5) = P(258) = .223

B(1) = P(254) = -2.080

A = P(253) = 1.000

- B(6) = P(259) = .693
- B(7) = P(260) = 1.250
- B(8) = P(261) = 2.080

#### ITEM 30 9 GRADED CATEGORIES

#### A = P(262) = 1.000

- B(1) = P(263) = -2.080
- B(2) = P(264) = -1.250
- B(3) = P(265) = -.693
- B(4) = P(266) = -.223
- B(5) = P(267) = .223
- B(6) = P(268) = .693
- B(7) = P(269) = 1.250
- B(8) = P(270) = 2.080

#### ITEM 31 9 GRADED CATEGORIES

#### A = P(271) = 1.000

- B(1) = P(272) = -2.080
- B(2) = P(273) = -1.250
- B(3) = P(274) = -.693
- B(4) = P(275) = -.223
- B(5) = P(276) = .223
- B(6) = P(277) = .693
- B(7) = P(278) = 1.250
- B(8) = P(279) = 2.080

# ITEM 32 9 GRADED CATEGORIES

#### A = P(280) = 1.000

- B(1) = P(281) = -2.080
- B(2) = P(282) = -1.250
- B(3) = P(283) = -.693
- B(4) = P(284) = -.223
- B(5) = P(285) = .223
- B(6) = P(286) = .693
- B(7) = P(287) = 1.250
- B(8) = P(288) = 2.080



# ITEM 33 9 GRADED CATEGORIES

A = P(289) =	1.0	00
B(1) = P(290)	=	-2.080
B(2) = P(291)	=	-1.250
B(3) = P(292)	=	693
B(4) = P(293)	=	223
B(5) = P(294)	=	.223
B(6) = P(295)	=	.693
B(7) = P(296)	=	1.250
B(8) = P(297)	=	2.080

# ITEM 34 9 GRADED CATEGORIES

A = P(298) = 1.00	00
B(1) = P(299) =	-2.080
B(2) = P(300) =	-1.250
B(3) = P(301) =	693
B(4) = P(302) =	223
B(5) = P(303) =	.223
B(6) = P(304) =	.693
B(7) = P(305) =	1.250
B(8) = P(306) =	2.080

#### ITEM 35 9 GRADED CATEGORIES

A = P(307) = 1.000
B(1) = P(308) = -2.080
B(2) = P(309) = -1.250
B(3) = P(310) =693
B(4) = P(311) =223
B(5) = P(312) = .223
B(6) = P(313) = .693
B(7) = P(314) = 1.250
B(8) = P(315) = 2.080

# ITEM 36 9 GRADED CATEGORIES

A = P(316) = 1.00	00
B(1) = P(317) =	-2.080
B(2) = P(318) =	-1.250
B(3) = P(319) =	693
B(4) = P(320) =	223
B(5) = P(321) =	.223
B(6) = P(322) =	.693
B(7) = P(323) =	1.250
B(8) = P(324) =	2.080

# ITEM 37 9 GRADED CATEGORIES

```
A = P(325) = 1.000

B(1) = P(326) = -2.080

B(2) = P(327) = -1.250

B(3) = P(328) = -.693

B(4) = P(329) = -.223

B(5) = P(330) = .223

B(6) = P(331) = .693

B(7) = P(332) = 1.250

B(8) = P(333) = 2.080
```

# ITEM 38 9 GRADED CATEGORIES

A = P(334) = 1.0	00
B(1) = P(335) =	-2.080
B(2) = P(336) =	-1.250
B(3) = P(337) =	693
B(4) = P(338) =	223
B(5) = P(339) =	.223
B(6) = P(340) =	.693
B(7) = P(341) =	1.250
B(8) = P(342) =	2.080

# ITEM 39 9 GRADED CATEGORIES

A = P(343) = 1.0	00
B(1) = P(344) =	-2.080
B(2) = P(345) =	-1.250
B(3) = P(346) =	693
B(4) = P(347) =	223
B(5) = P(348) =	.223
B(6) = P(349) =	.693
B(7) = P(350) =	1.250
B(8) = P(351) =	2.080

# ITEM 40 9 GRADED CATEGORIES

A = P(352) =	1.000	
B(1) = P(353)	= -2	.080
B(2) = P(354)	= -1	.250
B(3) = P(355)	=	693
B(4) = P(356)	= -,	223
B(5) = P(357)	= .	223
B(6) = P(358)	= .	693
B( 7) = $P(359)$	= 1	.250
B(8) = P(360)	= 2	.080



#### ITEM 41 9 GRADED CATEGORIES

A = P(361) = 1.000 B(1) = P(362) = -2.080 B(2) = P(363) = -1.250 B(3) = P(364) = -.693 B(4) = P(365) = -.223 B(5) = P(366) = .223 B(6) = P(367) = .693

B(7) = P(368) = 1.250

B(8) = P(369) = 2.080

# ITEM 42 9 GRADED CATEGORIES

# A = P(370) = 1.000 B(1) = P(371) = -2.080 B(2) = P(372) = -1.250 B(3) = P(373) = -.693 B(4) = P(374) = -.223 B(5) = P(375) = .223 B(6) = P(376) = .693 B(7) = P(377) = 1.250 B(8) = P(378) = 2.080

# ITEM 43 9 GRADED CATEGORIES

A = P(379) =	1.000
B(1) = P(380)	= -2.080
B(2) = P(381)	= -1.250
B(3) = P(382)	=693
B(4) = P(383)	=223
B(5) = P(384)	= .223
B(6) = P(385)	= .693
B(7) = P(386)	= 1.250
B(8) = P(387)	= 2.080

### ITEM 44 9 GRADED CATEGORIES

A = P(388) = 1.	000
B(1) = P(389) =	-2.080
B(2) = P(390) =	-1.250
B(3) = P(391) =	693
B(4) = P(392) =	223
B(5) = P(393) =	.223
B(6) = P(394) =	.693
B(7) = P(395) =	1.250
B(8) = P(396) =	2.080

#### ITEM 45 9 GRADED CATEGORIES

```
A = P(397) = 1.000

B(1) = P(398) = -2.080

B(2) = P(399) = -1.250

B(3) = P(400) = -.693

B(4) = P(401) = -.223

B(5) = P(402) = .223

B(6) = P(403) = .693

B(7) = P(404) = 1.250

B(8) = P(405) = 2.080
```

#### ITEM 46 9 GRADED CATEGORIES

A = P(406) = 1.0	00
B(1) = P(407) =	-2.080
B(2) = P(408) =	-1.250
B(3) = P(409) =	693
B(4) = P(410) =	223
B(5) = P(411) =	.223
B(6) = P(412) =	.693
B(7) = P(413) =	1.250
B(8) = P(414) =	2.080

# ITEM 47 9 GRADED CATEGORIES

A = P(415) = 1.0	000
B(1) = P(416) =	-2.080
B(2) = P(417) =	-1.250
B(3) = P(418) =	693
B(4) = P(419) =	223
B(5) = P(420) =	.223
B(6) = P(421) =	.693
B(7) = P(422) =	1.250
B(8) = P(423) =	2.080

# ITEM 48 9 GRADED CATEGORIES

A = D(424) =	1 ^	^^
A = P(424) =		UU
B(1) = P(425)	=	-2.080
B(2) = P(426)	=	-1.250
B(3) = P(427)	=	693
B(4) = P(428)	=	223
B(5) = P(429)	=	.223
B(6) = P(430)	=	.693
B(7) = P(431)	=	1.250
B(8) = P(432)	=	2.080



#### ITEM 49 9 GRADED CATEGORIES

A = P(433) = 1.000B(1) = P(434) = -2.080B(2) = P(435) = -1.250B(3) = P(436) = -.693B(4) = P(437) = -.223B(5) = P(438) =.223 B(6) = P(439) =.693 B(7) = P(440) = 1.250

B(8) = P(441) = 2.080

#### ITEM 50 9 GRADED CATEGORIES

A = P(442) = 1.000B(1) = P(443) = -2.080B(2) = P(444) = -1.250B(3) = P(445) = -.693B(4) = P(446) = -.223B(5) = P(447) =.223 B(6) = P(448) =.693 B(7) = P(449) = 1.250B(8) = P(450) = 2.080

# ITEM 51 GRP1 GAUSSIAN CONTINUOUS-

BETA = P(499) = -1.000, MU = P(451) = .000, SIGMA = P(498) = 1.000

IN-CORE CATEGORICAL DATA STORAGE AVAILABLE FOR N = 500, 5000 WORDS.

SCHOOL D

READING DATA... KEY-CODE CATEGORY

- 1

- 5
- 7

FORMAT FOR DATA-(4A1,1X,48A1,T5,F1.0)

FIRST OBSERVATION AS READ-

**NORML** .000



SCHOOL D

				S	CORING DA SCHOOL						
			ID		SCHOOL		ID				ID
THETAHAT	S.E.	ITER	FIELD	THETAHAT	S.E.	ITER	FIELD	THETAHAT	S.E.	ITER	FIELD
586	.389	5	1	115	.360	2	70	. 273	.368	4	139
687	.608	5	2	.000	1.000	1	71	331	.459	4	140
.400	.370	4	3	056	.354	2	72	. 275	.391	4 2	141
698 880	.456 .391	4	4 5	638	.422 .774	4 2	73 74	204 .319	.363 .378	4	142 143
.037	.408	2	6	133 .579	.365	4	74 75	894	.428	3	143
635	.390	3	7	-1.861	.438	4	76	-1.295	.410	4	145
.192	.464	4	8	813	.363	3	77	217	.443	2	146
.307	.390	4	9	.000	1.000	ĭ	78	325	.382	4	147
-1.010	.492	3	10	.502	.342	3	79	094	.376	3	148
-1.350	.834	6	11	.166	.387	4	80	601	.383	4	149
.336	.369	4	12	-1.891	.435	3	81	.000	1.000	1	150
-1.258	.554	4	13	.116	.323	4	82	717	.399	4	151
295	.436	3	14	.481	.366	4	83	.302	.366	4	152
613	.366 .502	5 5	15 16	-1.034 751	.783 .472	3 4	84 85	-1.064	.379	4 2	153
-1.483 682	.378	4	17	751	.363	4	86	.031 970	.375 .642	4	154 155
-1.255	.506	4	18	-2.096	.509	3	87	570	.398	4	156
431	.346	4	19	175	.443	4	88	602	.617	2	157
606	.438	4	20	660	.342	4	89	.000	1.000	ĩ	158
725	.427	3	21	.093	.374	2	90	-1.091	.530	5	159
-1.185	.511	3	22	.081	.426	2	91	. 729	.353	5	160
.000	1.000	1	23	717	.357	4	92	276	.352	3	161
.079	.345	2	24	140	.397	2	93	.000	1.000	1	162
352	.422	4	25	958	.471	5	94	603	. 376	4	163
.189	.348	4	26	402	.346	4	95	.000	1.000	1	164
-2.034	.524	4	27 28	614	.415	4	96	408	.407	4	165
526 478	.409 .462	4	28 29	245 -1.023	.332 .488	4	97 98	.000 .158	.351 .344	1 4	166 167
478	.375	2	30	.220	.444	4	99	-1.351	.410	3	168
.000	1.000	ĩ	31	-1.005	.385	4	100	840	.776	3	169
906	.340	5	32	.838	.364	5	101	.000	1.000	ĭ	170
.181	.369	4	33	238	.367	2	102	094	.374	4	171
770	.620	2	34	750	.359	4	103	507	.344	4	172
-1.466	.499	3	35	.411	.376	4	104	038	.410	4	173
833	.419	3	36	425	.693	4	105	376	.360	4	174
914	.624	4	37	.148	.365	4	106	417	.395	4	175
-1.240 .196	.462 .354	5 4	38 39	198	.385	4	107	142	.357	4	176
-1.120	.388	4	40	.105 089	.344 .447	4 3	108 109	546 650	.390 .372	4 3	177 178
952	.418	4	41	313	.832	4	110	-1.706	.429	4	178
-1.539	.425	3	42	.000	1.000	i	111	.369	.356	4	180
.705	.357	5	43	222	.408	2	112	763	.358	5	181
726	.379	4	44	381	.376	4	113	899	.668	4	182
-1.428	. 721	3	45	770	.536	3	114	647	.376	5	183
756	.457	4	46	-1.057	.391	3	115	227	.712	4	184
700	.404	4	47	223	.354	4	116	000	.468	4	185
-1.261	.411	5	48	.000	1.000	1	117	-1.396	.414	5	186
-1.758	.410 .410	5 5	49 50	.098	.384	4	118	. 000	1.000	1	187
-1.110 314	.375	4	50 51	-1.129 -1.071	.401 .431	5 3	119 120	. 233	.722	4	188
.353	.347	4	52	-1.128	.462	3	121	653 066	.599 .385	4	189
.137	.392	4	53	211	.368	4	122	.000	1.000	ì	190 191
468	.401	4	54	.000	1.000	i	123	740	.378	4	192
. 029	.360	2	55	.217	.402	4	124	518	.368	3	193
-1.149	.432	5	56	971	.408	4	125	511	.376	3	194
615	.360	4	57	.000	1.000	1	126	-1.128	.445	4	195
.084	.355	2	58	196	.356	3	127	952	.578	4	196
-1.670	.456	3	59	.340	.467	4	128	-1.333	.479	3	197
582	.532	5	60	828	.373	3	129	063	.377	2	198
.000	.545	1 2	61 62	495	.522	4	130	.468	.384	4	199
276 136	.455 .349	2	62 63	716 .100	.371 .388	4	131	-1.014	.422	3	200
217	.443	2	64	399	.334	4	132 133	968 665	.385 .457	4	201 202
-1.560	.383	4	65	.027	.348	2	134	834	.633	4	202
143	.359	2	66	764	.388	5	135	349	. 417	4	204
293	.362	4	67	-1.512	.458	3	136	346	.359	4	205
983	.385	3	68	.000	1.000	ī	137	.000	1.000	i	206
.157	.420	4	69	357	.350	4	138	DATA ARE		2	

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Appendix B



COPYRIGHT (C) 1984,1988 SAS INSTITUTE INC., CARY, N.C. 27512, U.S.A. THE JOB NEWARK HAS BEEN RUN UNDER RELEASE 5.18 OF SAS AT RUTGERS UNIVERSITY- CCIS (01449001). **0S SAS 5.18** SAS(R) LOG NOTE: NOTE:

MODEL = 3081 MODEL = 3081 SERIAL = 024071 SERIAL = 024071 VERSION - FF VERSION - FF CPUIO CPUIO NOTE:

NOTE: SAS OPTIONS SPECIFIED ARE:

SORT-4 LEAVE-24K

5′: LAW SCHOOL DATA'; TITLE2 'GENERAL LINEAR MODEL STUOY'; TITLE3 'ALL STUDENTS, MINIMUM COURSE SIZE OPTIONS LINESIZE-80; INPUT IO 1-6; OD COURSE=1 TO 158; INPUT (GRADE) (2.) 0; IF GRADE EQ O THEN GRADE=.; INFILE FILE2; DATA WORK1; OUTPUT: TITLE 1 5 4 5 5 5 7 8 5 7 8 5 7 8 9 P 8

OSNAME=WYL.A2543.SOO1.SCHOOL23.MATRIX, UNIT=DISK,VOL=SER=WYL8O1,DISP=SHR, DCB=(BLKSIZE=4000.LRECL=80,RECFM=FB) INFILE FILE2 IS: NOTE:

SAS WENT TO A NEW LINE WHEN INPUT STATEMENT
REACHED PAST THE END OF A LINE.
1030 LINES WERE READ FROM INFILE FILE2.
DATA SET WORK.WORK1 HAS 32548 OBSERVATIONS AND 3 VARIABLES. 1676 OBS/TRK.
THE DATA STATEMENT USED 1.30 SECONDS AND 196K. NOTE: NOTE:

NOTE:

PROC GLM;

LSMEANS ID COURSE / STDERR; PROCEDURE GLM USED 188.97 SECONDS AND 420K PRINTED PAGES 1 TO 18. CLASS IO COURSE; MODEL GRADE-IO COURSE; MEANS IO COURSE; NOTE: 5 9 7

SAS USED 420K MEMORY. ANO NOTE:

SAS INSTITUTE INC SAS CIRCLE NOTE:

PD BDX 8000 CARY, N.C. 27512-8000

# LAW SCHOOL DATA GENERAL LINEAR MODEL STUDY

ALL STUDENTS, MINIMUM COURSE SIZE = 5

14:13 MONDAY, JUNE 10, 1991

#### GENERAL LINEAR MODELS PROCEDURE

#### CLASS LEVEL INFORMATION

CLASS	LEVELS	VALUES
10	206	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198 199 200 201 202 203 204 205 206
COURSE	158	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 68 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158

NUMBER OF OBSERVATIONS IN DATA SET - 32548

NOTE: ALL DEPENDENT VARIABLES ARE CONSISTENT WITH RESPECT TO THE PRESENCE OR ABSENCE OF MISSING VALUES. HOWEVER, ONLY 3517 OBSERVATIONS CAN BE USED IN THIS ANALYSIS.

# LAW SCHOOL OATA GENERAL LINEAR MODEL STUDY ALL STUDENTS, MINIMUM COURSE SIZE = 5

14:13 MONDAY, JUNE 10, 1991

GENERAL LINEAR MODELS PROCEDURE

DEPENDENT V	ARIABLE: GRADE			
SOURCE	OF	SUM OF SQUARES	MEAN SQUARE	F VALUE
MODEL	345	97584.57348241	282.85383618	3 10.77
ERROR	3171	83242.59114653	26.25121134	PR > F
CORRECTED. TO	DTAL 3516	180827.16462895		0.0
R-SQUARE	c.v.	ROOT MSE	GRADE MEAN	i
0.539657	16.9912	5.12359360	30. 15439295	<b>5</b>
SOURCE	OF	TYPE I SS	F VALUE PR > F	•
IO COURSE	188 157	62846.00198850 34738.57149391	12.73 0.0 8.43 0.0	
SOURCE	OF	TYPE III SS	F VALUE PR > F	•
IO COURSE	188 157	61636.42752878 34738.57149391	12.49 0.0 8.43 0.0	



# ₽. GENERAL LINEAR MODELS PROCEDURE $^{2}$ LAW SCHOOL DATA GENERAL LINEAR MODEL STUDY ALL STUDENTS, MINIMUM COURSE SIZE = 0833333 8333333 8333333 3000000 0000000 1818185 1727273 17727273 15000000 16383636 17727273 17727273 1 .5000000 6111111 .3333333 .529418 .3333333 .0000000 .5230769 .5000000 .6190478 .1578947 .3600000 .3571429 448807-864-6684-6686-6686-6886-688-688-6886-688

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350100	Z	GRAOE	GENERAL LIV	L LINE	GENERAL LINEAR MODELS PROCEDURE	5.	MONDAY, JUNE	NE 10, 1991
		28 5303867	_	MEANS			MEANS	
- 64 (	176	0,1	COURSE	z	GRADE	2000	2	0.00
n <b>⊲</b>	133	29.0390625	é	!		COORSE	2	7000
מני	125	29.0320000	50 C	2:	34.5882353	108	∞	36.3750000
•	124	28.2419355	n C	<u> </u>	31.5000000	109	∞	37.0000000
1	122	27.0245902	9-9	4	24.8571429	9	<b>c</b>	30.000000
∞	121	32.1900826	62	<u> </u>	38.3846154		<b>80</b> (	27.1250000
6	10	_	63	Ē	28.4615385	112	<b>2</b> Ο α	33 3750000
₽:		29.4533333	64	<u>.</u>	32.0000000	4-	-	30.000000
- :	4 4 0 4	29 6458333	92	<u>ლ</u> :	28.2307692	115	_	32.0000000
7 5	47	29.4255319	99	2 5	26.1666667	116	7	32.2857143
4	47	34,6595745	· «	2 2	33.2500000	117	7	33.8571429
ī.	4	25.0909091	69	2 0	28 5833333	118	۲ -	32.2857143
16	44	24.9772727	02	! =	37.4545455	119		33.0000000
11	7	28.4634146	7.	=	26. 1818182	2 5		34 2857143
Φ :	<b>4</b> 4	24.6/30000	72	= :	31.1818182	122		35.1428571
9.0	\$ 6	26 850000	E .	Ξ:	31.6363636	123	9	32.333333
2.6	) 6 7	31.6153846	4 L	= :	36.8181818	124	g	29.0000000
22	37		76	= :	34.4343433	125	9	32.1666667
23	37	28.9459459	77	: :	30.18182	126	ဖ ဖ	34.833333
24	37	25.8378378	78	=	25.8181818	127	<b>1</b> 0 0	29.8333333
25	37	31.4864865	79	ō	36.4000000	971	o cc	35,0000000
26	9 8	29.383333	<b>8</b>	6	34.111111	90	ω (	35.000000
77	n e		- 6	۹ و	34.0000000	131	တ	36.1666667
0 60	3 5	29.0000000	20	2 9	38.4000000	132	ဖ	34.1666667
300	58	28.2068966	8 6	2 9	30.70000	133	ဖ ဖ	32.1666667
31	58	28.9655172	82	9	35.6000000	4 10.4	ט פ	31 5000000
32	7 9	25. /500000	98	6	28.555556	136	<b>•</b>	26.666667
	27	27.7407407	280	<b>6</b> 1	28.444444	137	9	31.6666667
7 107	56	28.7692308	D 0	on (	28.222222	138	9	28.833333
36	56	29.5000000	66	n on	33.444444 34.444444	139	φ <b>•</b>	26.6666667
37	<b>5</b> 0	36.8461538	-6	0	29.6666667	04.	4 R	34.2500000
90 c	2, c U R	34 0000000	92		31.444444	142	מי	31.4000000
40	24	27.3750000	693		32.555556	143	ß	32,6000000
=	24	27.6666667	ים מים		32.111111	144	ហ	26.8000000
77	5 5	30.6250000	96		29. 777778	145	រោម	22.000000
4 4 5 4	9 C	34.5909091	97		27.555556	140	ט מ	34.000000
4 4 10 10 10 10 10 10 10 10 10 10 10 10 10 1			86		30.777778	4 4	חנ	38.00000
46	6-	36,0526316	66	∞	36.0000000	149	e un	28.600000
47	2	•	8 3	∞ .	34.1250000	150	· w	32.4000000
48	50		5 5		34.1250000	151	ß	38.8000000
49	8	27.5000000	202		34.6250000	152	IO I	35.4000000
<b>0</b>	6 .	•	40		31.3750000	153	ព	29.8000000
181 1	<u> </u>	30.6642103	105		29.2500000	10 4 8 8	n u	36.500000
7 6	<u>.</u> <u>.</u>	27.9473684	90		38.6250000	2 2	) <b>8</b> 7	31.200000
5 TO 10	<u>.</u>	31,2631579	107		37.6250000	157	) <b>a</b> n	21.200000
100	. 6	29.722222				158	NO.	
86	18	33.777778						
67	11	30.7058824						

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LAW SCHOOL DATA
GENERAL LINEAR MODEL STUDY
ALL STUDENTS, MINIMUM COURSE SIZE = 5
14:13 MONOAY, JUNE 10, 1991
GENERAL LINEAR MODELS PROCEDURE

WEANS	STD ERR PROB 5 TI		439805 0.0 E14260 0.0	ö	ö	ö	142895 0.0	1239576 0.0	7208211 0.0001	0	.2765707 0.0	0943939 0.0	4981020 0.0	_	0.0 0.0	•	3535797 0.0	0.0002182	2970730 0.0		0.0791123 0.0	2210969 0.0	1435366 0.0	.2843760 0.0	1393003 0.0	2138238 0.0	4524176 0.0001	Ö	0	5863337 0.0		4627119 0.0	0740275 0.0	ö	1577869 0.0	ó	ö	.0	- (	.1367388 0.0	2486511 0.0	
LEAST SQUARES MEANS	GRAOE ST			36.2/32092	9761554 1.1	-	-	<u>-</u> .	25.0341456 1.12	-	<del>-</del>	≟.	<b>∴</b> •	26.11.72888 1.09	7427985 1.	-	<b>-</b>	6347629 1.	35.2495178 1.40 28.8250670 1.29	1736270	- •	24.0221206	-	- •	36.0690114 1.13	0126964 1.	23.3871147 3.63	: -:	<b>-</b>	<u>-</u> -	31.4363161	: -	-	-	<b>∴</b> •	31.6908298 1.0	-	-	<b>-</b>	- •	40.7942285 1.02 32 4885563 1.24	
			52		ត សេ ភ ហ	56	57	58	6 G	9	62	63	64	6 G	90	89	69	<b>10</b>	7.2	47	75	76	62	80	<del>-</del> c	83	400 C	n ee		888	5 C	O T	8 6	66	<b>46</b>	90 C	96	- ex	66	8	- CO-	! > .
	PROB > T	0.0	0.000	9.0	0.00	0.0	0.0	0.0	0.0	586		0.0	0.0		0.000	50.00	0.0	0.0	0.0		0.0	000	300	0.0	0.0	000	•	0.00		0.0	•	•	9.0			•	•					
SQUARES MEANS	STO ERR LSMEAN	1.0779139	2.5742994	1.24014/3	1,1895395	1.2761211	1,1463727	1.8241751	1.3153728	1.4634838	1 1665063	1.2237671	1.2104586	1.0780529	1.3903400	1.0748720	1,1752542	1.1094458		1.2790796	: <b>-</b> :	-	1.522096/	1.2494948	1.0997013	1.0494990	N		1.0616077	1,2136635	1.2040848	1,1392793	1.4077157	1 1043021	1, 1235075	2.1263366	1.1511599	1.0968061	1.1533073	1.12083307	1.1491516	
LEAST	GRADE	29.9848628	26.9668297	38.0430877	28.1095127	35.8411432	31.0913818	36.4078339	38.3171948	25.3374343	19.0757939	23 9805509	; -:	29.9003730	23.6136985	30.6746022	32,0871209	31.6459140	27.6479098	26.5146406	32, 1501091	35.3199333	22.4091184	28.7156055		28.8758676		23.5076660	27.9098101			26.9165598	29.4884028			20.7030042	28.6919326	æ	•	24.8060069	32.2485264	

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LAW SCHOOL DATA
GENERAL LINEAR WODEL STUDY
ALL STUDENTS, MINIMUM COURSE SIZE = 5
14:13 MDNDAY, JUNE 10, 1991
GENERAL LINEAR MODELS PROCEDURE

			ALL STUDENTS, MINIMUM COURSE SIZE 14 GENERAL LINEAR MODELS PROCEDURE	COURSE SIZE = 5 14:13 MDNDAY, JUNE LS PROCEDURE	AY, JUNE 10, 199	91	
	LEAST	SQUARES MEANS					
9	GRADE	STD ERR LSMEAN	PROB >  T  HO:LSMEAN=O	01	LEAST : GRADE	LEAST SQUARES MEANS RADE STD ERR	PROB > 11
5	30, 1251851	1.0732954	C C		LSMEAN	LSMEAN	ш
\$		1,1468557	0.0	685	23,4621746	1.3951256	0.0001
105	25.6525152	1.8912375	0.0001	160		1.1216552	0.0
<u>8</u>		1.0974111	0.0	161	32.2362842	1.0594997	0.0
5 5	34 1745309	1.1497718	0.0	163	31,2938753	1.2860712	0.0
2 5	35.40212/4	1.7208211		165	28.0458321	1.1830821	0.0
2 2	23.8871147	3.6356783	.000	166	35.0509937	1.1279466	•
112	32.4999711	1.1287237	0.0	167	37.4164001	1.1211795	0 0
113	32.8385890	1.1420617	0.0	169	20.7737729	2.9706116	000
4 :	26.3214053	1.7250726	0.0001	171	34.5355095	1.2663200	
113	28.2018380	1.2341018	0.0	172	31.1332282	1.1371119	0.0
- <del>-</del>	36.6433361	1.1512530		173	33.8608004	1.2906841	0.0
19	27.7466039	1.1156631	0.0	174	31.8993/61	1.16/4155	0 0
120	26.7748482	1.1017501	0.0	176	33,1446157	1.1746197	9 6
121	23.9570543	1.1005848		171	31.8920266	1.1236456	0.0
122	32.7216577	1.1506266		178	30.2099605	1.1183331	0.0
4 2 4 2 8 C 4	36.884/80/	1.14/5863	9.0	179	24.5503940	1.1769774	
127	33.6868601	1.1418296	0.00	087	37.3053713	1.1132338	00
128	37.4716142	1.7208211	0.0	182	25.4971942	2.8754462	
129	30.2020786	1.0941969	•	183	29.3525904	1.2414106	0.0
2 5	29.5274695 28.4696860	1.12/516/	50.0	184	30.2023182	2.3880777	0.001
132		1.1740117	0.0	5 C C	35.0271698 27.0624334	1.7208211	0 0
133	31.6245881	1.1165383		88	38.3871147	3.6356783	
134	34.7346232	1.0760022		189	29, 1698351	2.3040965	0000
33	26.3864180	1.0693498	0.0	190	34.1096271	1.2051962	0.0
138	33.3264144	1.1239016		192	30.3679327	1.0951325	0.0
139	36.4652616	1.2042278	0.0	76.	30.2982/48	1.0521613	0.0
140	30.4716142	1.7208211	0.0001	10 T	28.0760919	1.2032153	9 0
:	37.8449123	1.0980103	0.0	196	28.0229146	1.4194487	0.0
2 4 4 2 2	33.6115266	1.1216/11		197	24.0412433	1.1218134	0.0
144	28.6711023	1.2064734	) c		34.3608793	1.1484067	0.0
145		1.1471417	0.0	199	36.9127452	1.1762789	0.0
146		1.2741397	•	92.00	27.1513332	1.16/0607	0 0
147		1.1738414	•	202	30.1112053	1.2748854	9 0
<del>2</del> .		1.1499184	•	203	26.2168297	2.5742994	500
		1.1695431	0.0	204	29.4656409	1.1032848	0.0
152	310744	1.1448043	• -	205	31.6424871	1.0744288	0.0
153	901082	1.0951174					
154		1.1756039	0.0				
133		1.9715947	0.0001				
157	24.7248812	2.3264141	0.0 0.00 0.00				

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		•	GENERAL LINEAR	UOY			
		∢.	ALL STUDENTS, MINIMUM COURSE	512E = 5 14:13 MONDAY.	JUNE 10, 1991		
			GENERAL LINEAR MODELS				
	LEAST SQUAR	IARES MEANS			LEAST SOU	LEAST SQUARES MEANS	
OURSE	GRADE LSMEAN	STD ERR LSMEAN	PROB > [T] HO:LSMEAN=O	COURSE	GRADE	STD ERR LSMEAN	PROB >  T  HO:LSMEAN=O
	44.2	2818219	c	20	38.0335051	1.2093300	
	1	0.3877972	0	51	384847	1.2203720	0.0
	5		0 0	52	29,1469383	1.2089966	0.0
	2.5		0	53	27.5042639	1.2079211	0.0
	353		0.0	54	29.7253575	1.2074289	
	407		0.0	ល ល	29.9400317	1.2467179	0.0
	8	0.4789164	0.0	io i	34.2597583	1.2407182	
		0.4801823		/ n u	31.33911/8	1.292491/	
		0.5033994	0.0	20 C	34.1343303	1.2719850	9 6
0	29.7884563	0.6069430	0.0	n C	29.7397836 20.2398884	1.3440669	9.0
- (		0.7907548	9.0	9	26, 1684658	1.4158457	000
~ 0		0.7602066	9.0	6.2	37.0327638	1.4574702	
, .	29.77.0741	0.8006628		63	29.5961664	1,4663528	
. r	6445	0.8230349	0.00	64	29.2277775	1.4581194	0.0
œ	4297	0.8038393	0.0	65	27.7829361	1.4758671	0.0001
,	_	0.8368146	0.0	99	26.3578227	1.5183824	0.0001
. 60	718	0.8633913	0.0	29	30.7026763	1.5169967	
6	٠.	0.8611623	0.0	80 (F)	33.9448560	1.5182256	•
0	364	0.8325491	0.0	60	36 4005241	1.52/5440	5000
<u>.</u>	٠, ١	0.8743308	0.0	2.6	26. 1331608	1.5842670	
7	י פ	0.8669537	0.0	72	30, 5296877	1.5866924	
	28.448/643 26.7122655	0.86/2390	900	73	29.6567161	1.5854874	0.0001
, FU		0.8642408	0.0	74	36.1250627	1.5850037	0.0
, <b>(</b>	, 63	0.8767331	0.0	75	32.3463967	1.5845293	0.0
		0.8909253	0.0	76	29.3618658	1.5828739	0.000
	28.4797925	0.9196535		//	33.3718974	1.5836919	
6	26.8874304	0.9459209	0.0	7 7	20.3243316	1.0909380	9.00
0	26.5202908	0.9783175		n C	32 8217017	1 7564993	200
-	28.2060016	0.9765859	0.0	) ec	34.8419317	1.6631154	
~ ~	25.9655030	0.9939046	0.0	8 3	36.9896098	1.6600291	0.0
		1.0342.162		83	31.4609241	1.6611343	0.000
<b>1</b> 1	5 6	1 0305594	) C	80.4	32.5493624	1.6713176	0.0
, w		1.0590642		<b>8</b>	34.8730910	1.6619117	0.0
7	36.4703712	1.0331898	0.0	φ (		1.7517028	0.0001
80	27.8643374	1.0549392	0.0	<b>,</b> (	28.525265	1.7494007	0.0001
6	33.3518222	1.0517936		20 (C	27.7075308	1.7555151	0.000
0	26.0622816	1.0746924	0.0	ה ס	36.7740428	1.7493398	0.0
-	654037	1.0742291	0.0	<u> </u>	34.81/8754	1.7509583	0.0
~		1.0972827	0.0	- c	7991977.97	1.7535320	0.000
e -	66823	1.0980234	0.0	40.0	22 032133	1.7495290	500.0
<b>7</b>	387559	1.1206888	0.0	0 0	24.0743953	1.7400004	500.0
හ <sub>'</sub>	624445	1.1538734	0.0	u Q	29.3211890 36.6783566	1.7531/53	000.0
9 1	4549	1.2087791	0.0	n (p	31.0995760	1.7674898	9.0
_	377881	1.1465370		16	29 7353018	1 77 14329	58
<b>&amp;</b> (	. 51480	1.1772173	0.0		32,7005996	1.7639039	38
<b>5</b>	8.714988	1.1855547	). )	<b>&gt;</b>	•	>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>	



LAW SCHOOL DATA
GENERAL LINEAR MODEL STUDY
ALL STUDENTS, MINIMUM COURSE SIZE = 5
14:13 MONDAY, JUNE 10, 1991
GENERAL LINEAR MODELS PROCEDURE

	PROB > 11	0.0001	0.0001	0.000	999	000	0.000	0.0001	0.000	0.00	0.0001																															
LEAST SOUARES MEANS	STD ERR LSMEAN	2.3551798	2.3657867	2.3640325	2.351/392 2.351/392	2.3550174	2,3463369	2.3471837	2.3566174	2.3593119	2.3664268	•																														
LEAST SOU	GRADE	33.2000775	33.3525588	33.1012197	37 7162506	30,3747971	28.3167698	34.5104254	31.2503840	23.9907381	28.8567052																												÷			
	COURSE	148	149	150	- CR1	. E.	154	155	156	157	86.																															
	<b>0</b>	5.7	: =		<b>~</b>	<b>5</b> 2	=			-	_			: =	Ξ	=	Ξ.	Ξ:	= :	==	-	=	=	Ξ,	: :		-	Ŧ.	<del>.</del> .		<u>-</u>	_	<b>.</b>				_	_	_	-		
	PROB >  T  HO:LSMEAN=0	000	90.0	0.0	000.0	0.000	5 6 6 6		000	0.000	0.00	0.00		88	00.0	0.00	0.00	00.0	00.0	000	000	0.00	000.0	000	000	88	0.00	0.000	0 0		000.0	0.00	0.000			. 6		0.000	0.000	0.000	000	88
EAST SOUARES MEANS	STD ERR LSMEAN	1.8584573	1.8600274	1.8589969	1.8587360	1.8575224	1.8572463	1.8394034 4 8554054	1.8601773	1.8582839	1.8602415	1.8684202	1.8/12154	1.9871198	2.0073750	1.9836372	1.9862686	1.9883237	1.9853476	1.9852153	2.0004146	2.1456624	2.1458389	•	2.1423217	2.1712430	Τ.	•	2.1453511				2.1470250	2.1447076	2. 1550848	2.6325002	2.3496484	2.3501368	2.3512285	2.3452894	2.3625711	2.3518463
LEAST SOU	GRADE	33.5305217	įŘ	Ř	4	2	Š	39.23129/6	5 6	ĕ	õ	<u>ღ</u> ვ	26.4442001	. 4	7	Ö	Ď	<u> </u>	4	32.6394359	Ē	9	3	<u>-</u>	33.1786032	- 64	35, 1720917	33.8660042	34.4394526	36.2055361	33.0967902	34.0169309	25.9045068	31.0438930 20 6848788	26.7151034		"	•	28	7	9 2	35.1034285 36.5939826
	COURSE	66	3	102	103	104	105	2 5	چ چ	60	10		2 5	114	1.5	116	117	118	119	120	122	123	124	125	126	127	129	130	131	133	134	135	136	137	2 5	140	141	142	143	144	145	147

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